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Modeling and estimation of thermal conductivity of MgO–water/EG (60:40) by artificial neural network and correlation☆

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ABSTRACT

In this article, artificial neural network (ANN) model has been used to study the thermal conductivity of MgO–water/EG (60:40) nanofluids based on experimental data. MgO nanoparticles in a binary mixture of water/EG (60:40) were scattered to make the above-mentioned nanofluid in two stages. The properties of the nanofluid were measured in different concentrations (0.1, 0.2, 0.5, 0.75, 1, 2, and 3%) and temperatures of 20 to 50 °C. Afterwards, two correlations were suggested for predicting the thermal conductivity of the nanofluids. The results of this study show that the ANN model can predict thermal conductivity to a great degree and is in agreement with the experimental results.

1. Introduction

Low thermal conductivity of common liquids such as water, oil or ethylene glycol is a heat transfer disadvantage in solar energy, heat exchangers, nuclear reactors and electronic board cooling. In recent years, a number of studies have been done by different researchers which showed heat transfer in thermal devices can be enhanced by adding the nanoparticles (1–100 nm) to the above liquids [1–5].

Most researches revealed that the thermal conductivity of nanofluids is a function of shape and size of nanoparticles, solid volume concentration, and thermo-physical properties of base fluid and nanoparticles. A summary of existing experimental studies for the thermal conductivity enhancement of different nanofluids is listed in Table 1.

The experimental measurement of thermal conductivity of nanofluids is a costly and time-consuming process. Therefore, researchers have been encouraged to provide correlations for predicting the thermal conductivity of nanofluids. Mention may be made of the research studies of Chon et al. [21], Li and Peterson [22], Vajjha and Das [23], Duangthongsuk and Wongwises [24], Teng et al. [25], Ghanbarpour et al. [26] and Hemmat Esfe et al. [27–30].

Recently, in order to estimate accurately the thermal conductivity of nanofluids in different solid volume fractions, particle diameters and temperatures, there has been a concern in using soft computing methods to predict the thermal conductivity of nanofluids which are known as neural networks, genetic algorithms and fuzzy logic. A prediction of the thermal conductivity of different nanofluids, including SWCNTs in epoxy and poly methylmethacrylate and also MWCNTs suspended in oil, decene, water, ethylene glycol using the neural network method is obtained by Papari et al. [31].

Hojjat et al. [32] examined thermal conductivity of three different nanofluids: Al_2O_3, TiO_2, and CuO. Then, based on neural network, they modeled the experimental data using temperature and volume fraction of nanoparticles as input, and thermal conductivity of nanoparticles as output of neural network. Longo et al. [33] presented two neural network models for predicting the thermal conductivity of TiO_2/water and Al_2O_3/water nanofluids using the temperature, volume fraction, diameter of nanoparticle and particle thermal conductivity as the input variables. Hemmat Esfe et al. [34], based on experimental data, presented the thermal conductivity of MgO/EG nanofluids using artificial neural network (ANN). They considered the solid volume fraction, diameter of particle and temperature as the input data. Hemmat Esfe et al. [35] experimentally investigated the thermal conductivity of the ZnO/EG nanofluid and proposed a model for it. Then, a neural network was employed for modeling thermal conductivity of ZnO/EG nanofluid. Their results indicated that both model and ANN outputs are in good agreement with the experimental data. In another study, Hemmat Esfe et al. [36] used the results of several experiments to obtain the thermal conductivity of MWCNTs/water nanofluid. Based on the experimental data [28], they simulated the thermal conductivity of this nanofluid using artificial neural network, which led to a new correlation for predicting the thermal conductivity of COOH-functionalized MWCNTs/water nanofluid.

In this study, MgO nanoparticles are dispersed in a binary mixture of water and EG (40:60%) using two-step method. The main aim of the present article is to study the accuracy of artificial neural network method and correlation to modeling thermal conductivity of nanofluid at different temperatures and concentrations. Furthermore, the comparison between accuracy and reliability of correlation and ANN is performed.

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Table 1
A summary of existing experimental studies for the thermal conductivity enhancement of different nanofluids.

Authors	Base fluid	Dispersed particles	Maximum enhancement
Assael et al. [6]	Water	MWCNT	38.0%
Hwang et al. [7]	Water	MWCNT	11.3%
Amrollahi et al. [8]	EG	SWCNT	20.0%
Nanda et al. [9]	EG	SWCNT	35.0%
Glory et al. [10]	Water	MWCNT	64.0%
Jha & Ramaprabhua [11]	Water	Ag-MWCNT	37.3%
Chandrasekar et al. [12]	Water	Al_2O_3	10%
Liu et al. [13]	EG	MWCNT	12.4%
Harish et al. [14]	EG	SWCNT	14.8%
Sundar et al. [15]	Water	Fe_3O_4	48%
Jeong et al. [16]	Water	ZnO	21%
Hemmat Esfe et al. [17]	EG	MgO	46%
Hemmat Esfe et al. [18]	EG	$Mg(OH)_2$	23%
Li et al. [19]	EG	ZnO	13%
Hemmat Esfe et al. [20]	Water	MgO	22%

2. Design of an artificial neural network

ANN can be used to predict output data in systems which contain several input parameters. Human brain is a source of inspiration for ANN in processing data. A part of ANN called neurons can undertake processing data. You can find the following in the multi-layer perceptron neural network: input layer, hidden layer and output layer. In the present study, the behavior and thermal conductivity of MgO–EG/water nanofluid are modeled by ANN. The two input parameters are temperature (T) and solid volume fraction (φ) and the output parameter is the thermal conductivity (k).

Neuron is the smallest unit of neural network. In a neuron, input values are added with bias and then a function called transfer or activation function is applied on them. The output of a neuron can be calculated from its input through this function. Some ANN models are made up of several layers. There are several neurons in each layer which simply processes the data (see Eq. (1)).

$$y_k = \phi\left(\sum_{k=1}^{m} w_{ij}x_j + b_k\right) \tag{1}$$

where x_j is the input, y_k is the output, w_{kj} is the weight, b_k is the bias and ϕ represents the activation function.

In this modeling, the input dataset is divided into 3 parts: Train data, validation data and test data. 70% of dataset is regarded as train data; 15%, validation; and 15%, test data. The weight and biases of neurons are produced while training process is taking place. Validation data is used during training for tuning parameters of classifier and defining stopping criteria. In addition, it does not let the network over-fit. Over-fitting is a situation in which the error on the training dataset becomes too small (the new error is not small when new data is added to the model). It means that the ANN has memorized only the training examples, but new input values cannot be predicted correctly by network. The test dataset shows how well the ANN is trained.

Two hidden layers and an output one constitute the ANN in this modeling. A feed-forward multilayer perceptron neural network has been used to simulate the thermal conductivity of the MgO–EG/water nanofluid. The network will be trained with Levenberg–Marquardt backpropagation algorithm.

The number of neurons in the input and output layers was considered based on the output and input variables. The number of optimum hidden layers and the neurons of each hidden layer were concluded using the trial-and-error method. First, the structure of the hidden layer of the network starts with few neurons; then, the number of neurons was increased until the training error reached the lowest mean square error (MSE) and the mean absolute error (MAE). The MSE and MAE were calculated using the following equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(e_i)^2$$
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{2}$$
$$e_i = \frac{k_{nf}}{k_b}\Big|_{Exp} - \frac{k_{nf}}{k_b}\Big|_{Pred}$$

where e_i represents the difference between the measured experimental values and the model's estimated values and n is the number of data points. K_{nf} and K_b are the thermal conductivity of nanofluid and base fluid, respectively.

Table 2 shows the performance functions (MSE, MAE and regression values) for ANN with various structures.

According to this table, the two hidden layers with three neurons in the first hidden layer and four neurons in the second hidden layer are the optimal network structure for modeling the thermal conductivity of MgO–water/EG nanofluid. Fig. 1 shows the optimal structure of the neural network.

3. Result and discussion

ANN is used to predict thermal conductivity of MgO–EG/water nanofluids from input data such as temperature and volume fraction [37]. This data set is divided into 3 main subsets including train, validation and test. In the present study, the number of total experimental data was 56, 40 of which are regarded as training data, 8 of which are considered as validation data and the remaining data are referred to test data.

Fig. 2 demonstrates thermal conductivity versus temperature in different volume fractions. According to this figure, the thermal conductivity increases when temperature goes up. The enhancement of thermal conductivity due to an increase in temperature is noticeable when particle volume fraction increases. Also, for a given value of temperature it can be seen that thermal conductivity is an increasing function of volume fraction. This phenomenon can be attributed to the increase in

Table 2
Performance of neural network with different structures.

Number of hidden layer	Number of neuron in first hidden layer	Number of neuron in second hidden layer	MSE	MAE	R
1	3	0	5.23E − 05	0.0056	0.9958
	4	0	5.25E − 05	0.0055	0.9960
	5	0	4.79E − 05	0.0052	0.9962
	6	0	2.73E − 05	0.0027	0.9982
	7	0	3.68E − 05	0.0046	0.9970
	8	0	3.16E − 05	0.0044	0.9979
2	2	2	4.2E − 05	0.005	0.9962
	2	3	3.07E − 05	0.0041	0.9975
	2	4	2.7E − 05	0.0037	0.9978
	2	5	4.69E − 05	0.0053	0.9963
	2	6	2.92E − 05	0.0039	0.9963
	3	2	9.84E − 05	0.0075	0.9921
	3	3	3.28E − 05	0.0042	0.9976
	3	4	1.86E − 05	0.0032	0.9985
	3	5	3.04E − 05	0.0039	0.9976
	3	6	5.75E − 05	0.0041	0.9954
	4	3	4.78E − 05	0.0049	0.9969
	4	4	3.03E − 05	0.0043	0.9976
	4	5	2.47E − 05	0.0031	0.9982
	4	6	3.14E − 05	0.0036	0.9976
	5	3	4.05E − 05	0.0039	0.9962
	5	4	5.41E − 05	0.0052	0.9969
	5	5	1.88E − 05	0.0033	0.9985
	5	6	3.09E − 05	0.0042	0.9968

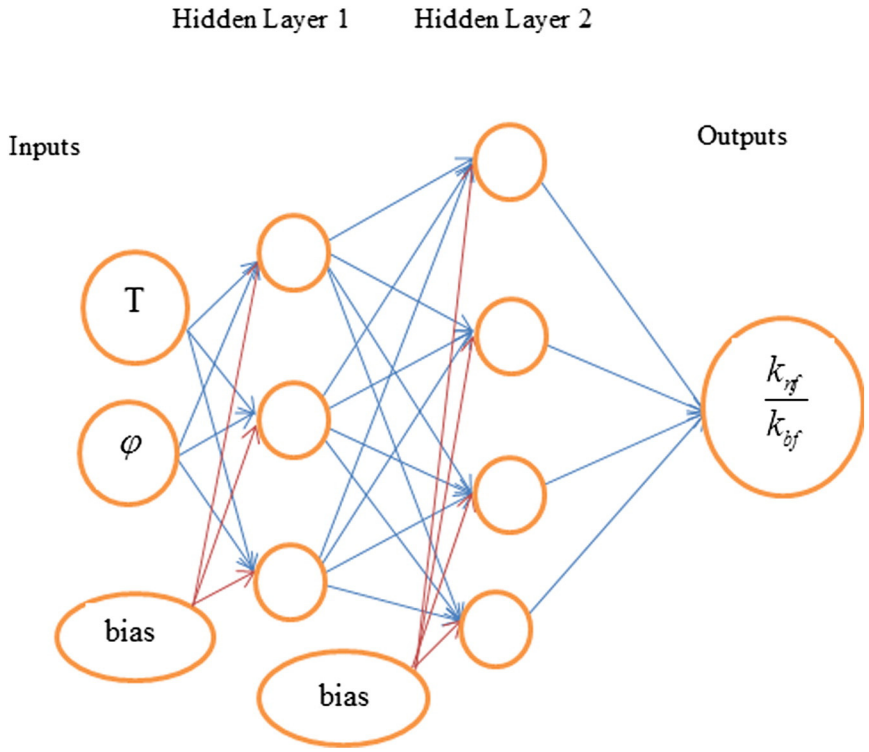

Fig. 1. Optimal structure of the neural network.

number of particles suspended in the base fluid (with a very high surface to volume ratio) and increase of Brownian motion.

Correlation between experimental values and predicted ANN outputs for thermal conductivity for all data set is shown in Fig. 3. As can be observed, most of the data are on the bisector or in its vicinity which presents a suitable correlation between experimental data and predicted outputs. This figure indicates the closeness among the experimental data and the predicted results using the ANN. Also, the maximum error (error is difference between experimental and predicted values) and MSE are 0.98% and 0.00001626, respectively.

Fig. 4 presents a comparison of the experimental results and predicted outputs of the neural network versus data number. It is evident from this figure that there is a good agreement between experimental data and predicted results.

Fig. 5 illustrates the variation of the relative thermal conductivity with solid volume fraction and temperature. As can be seen, the adaptation of the outputs of the neural network on experimental results is clearly shown. In this figure, the fitted curve corresponds well with experimental data. According to this figure the ANN is able to predict the thermal conductivity accurately. This is due to the use of different

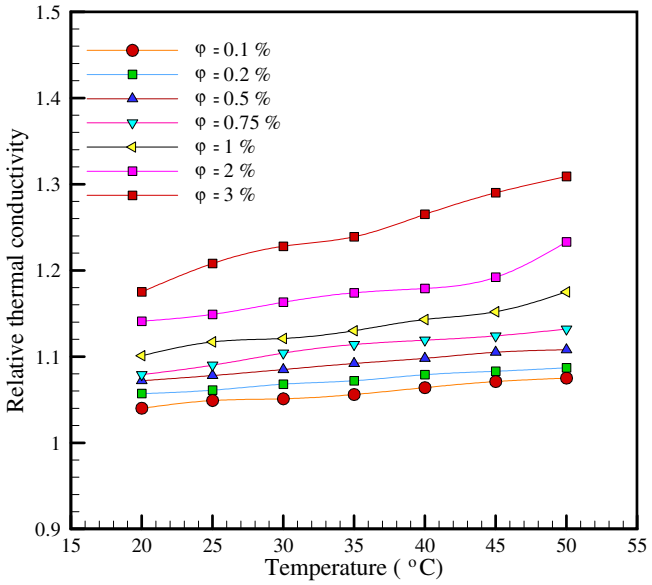

Fig. 2. Relative thermal conductivity of MgO–EG/water versus temperature for different concentrations.

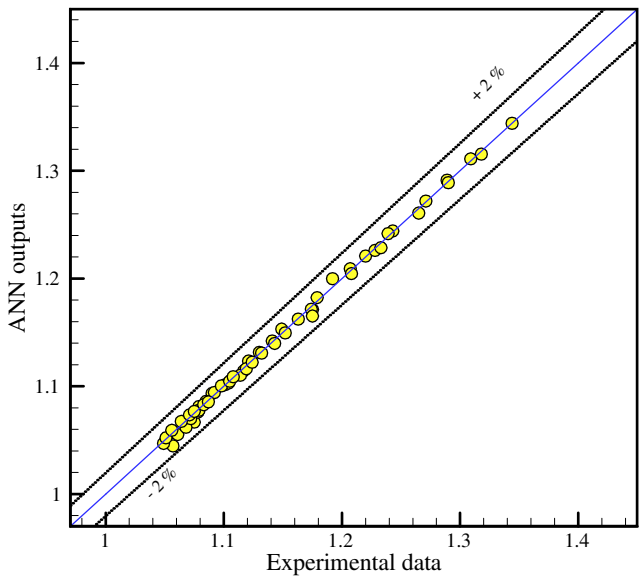

Fig. 3. Correlation between experimental values and predicted ANN outputs for thermal conductivity.

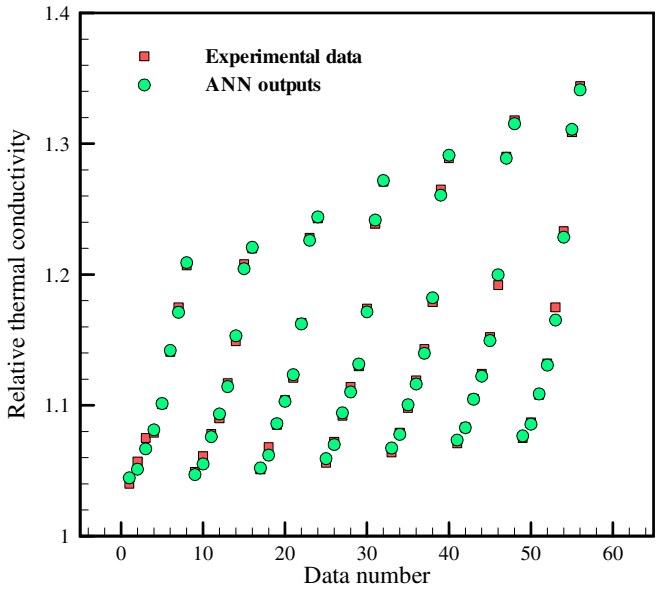

Fig. 4. Comparison between experimental data and predicted outputs of ANN for thermal conductivity.

hidden layers with different numbers of neurons to reach an optimal network.

4. Proposing correlation

As mentioned before, the thermal conductivity of MgO–water/EG nanofluid changes with variations in concentration of nanoparticles and temperature. Hence, the empirical correlation to predict the thermal conductivity of this nanofluid is proposed in Eq. (3) which is a function of solid volume fraction of nanoparticles and temperature. This correlation can be applied in the temperatures from 20 °C to 50 °C and volume fractions up to 3.0%.

$$\frac{k_{nf}}{k_{bf}} = 0.14314 \times Exp\left(\frac{-1.506}{\varphi} + 0.024656T\right) + 1.0664 \quad (3)$$

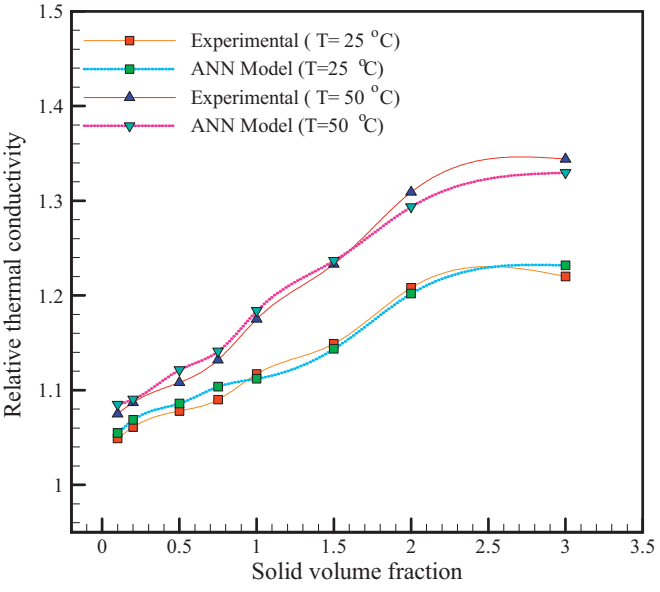

Fig. 5. Effect of solid volume fraction and temperature on the variation of thermal conductivity.

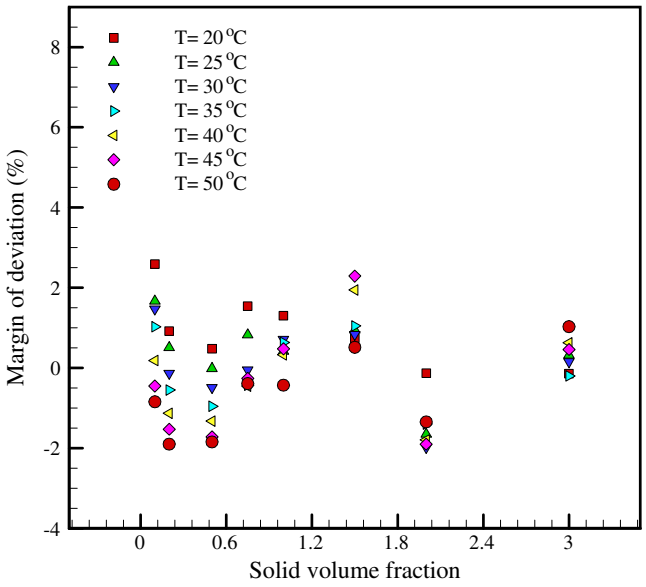

Fig. 6. Margin of deviation of the proposed correlation versus solid volume fraction.

5. Margin of deviation

In order to ensure the accuracy of the suggested correlation, the margin of deviation (MOD) can be defined as presented in Eq. (4):

$$MOD(\%) = \frac{K_{corr} - K_{exp}}{K_{exp}} \times 100 \quad (4)$$

where k_{corr} and k_{exp} are the thermal conductivity obtained through the correlation and experimental data, respectively. Fig. 6 shows the margin of deviation with respect to solid volume fraction at different temperatures. As can be seen, the MOD does not exceed 2.4 %, which exhibits the acceptable accuracy of the proposed correlation to estimate the thermal conductivity.

To display the compatibility between experimental findings and correlation outputs, comparison plots at different temperatures and various solid concentrations are shown in Fig. 7. As can be observed in

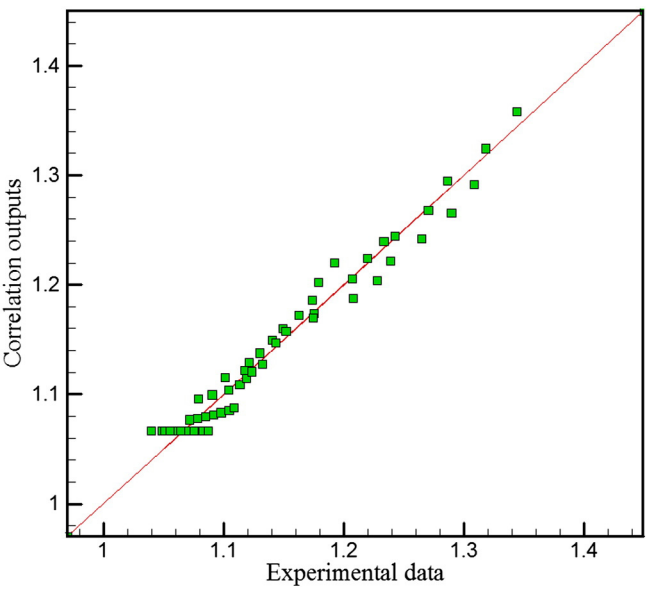

Fig. 7. Comparison between experimental data and values obtained from propose correlations.

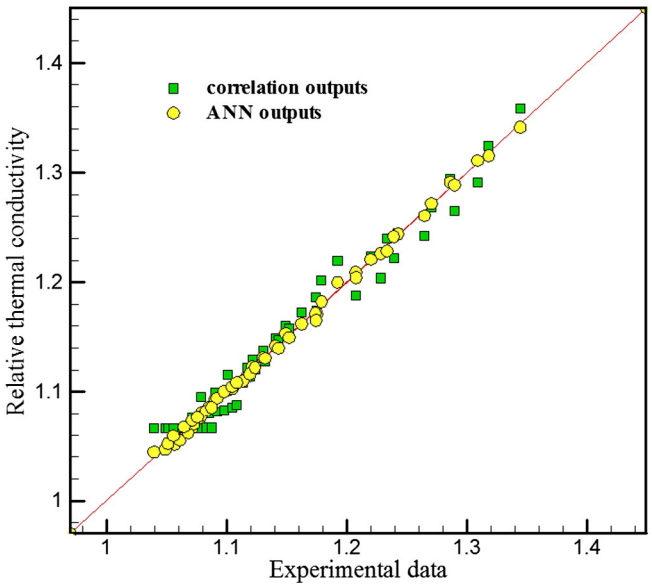

Fig. 8. Comparison between experimental data and values obtained from correlations and ANN.

all plots, the experimental data and correlation outputs are close to each other. This consistency shows that the proposed correlations can estimate the thermal conductivity well.

Fig. 8 exhibits a comparison between experimental data and values obtained from correlations outputs and ANN outputs. As can be observed, the predicted values for both models are in good agreement with the experimental data. Also, from this figure, ANN is able to estimate the thermal conductivity of MgO–water/EG at different volume fractions and temperatures with high precision.

6. Conclusion

In the present study, the behavior and thermal conductivity of MgO–EG/water nanofluid were modeled by ANN and proposed correlation based on experimental data. ANN and correlation were presented using experimental data. In ANN the two input parameters were temperature (T) and solid volume fraction (φ) and the output parameter was the thermal conductivity (k). 56 experimental data consisting of two parameters (seven different temperatures and eight various concentrations) were applied to model the thermal conductivity of nanofluid. The results showed that the predicted values for both models were in good agreement with the experimental data. Also, an artificial neural network can predict the thermal conductivity of nanofluid more accurately than the proposed correlation. Further investigations to elucidate the precise nature of this new class of heat transfer of nanofluids would be of considerable interest. The extension of this paper and our previous work [38–40] affords engineers a good option for nanofluid in different applications.

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